Deep Learning with MXNet Gluon

GLUON

Hongyuan Mei
Center for Language and Speech Processing
Department of Computer Science, Johns Hopkins University

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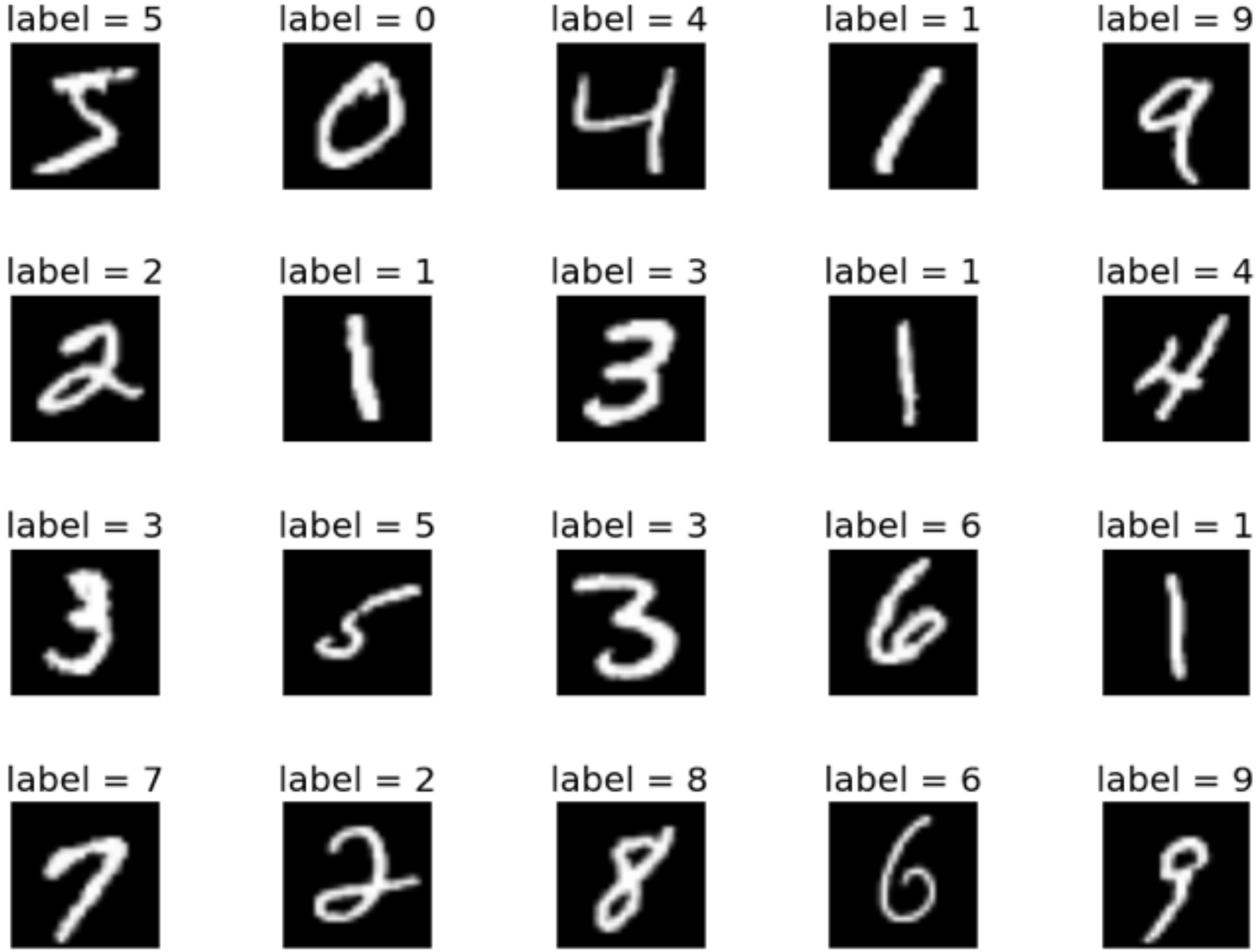
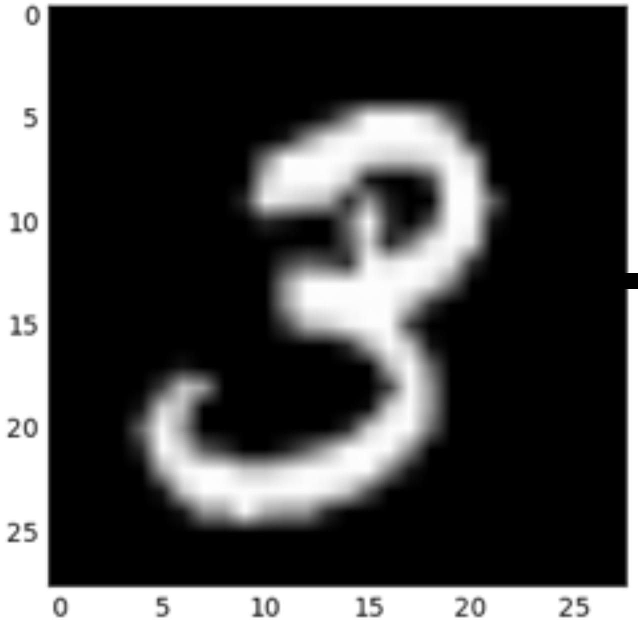
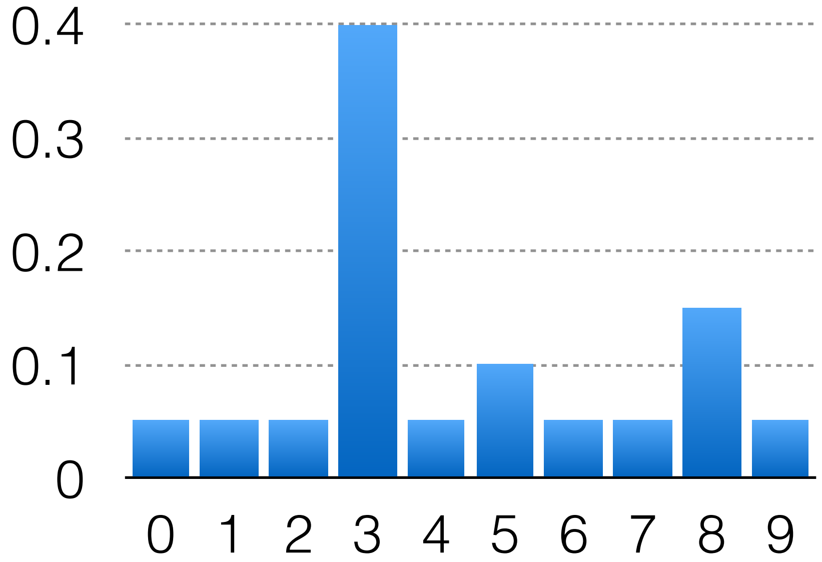
Supervised Learning



Supervised Learning

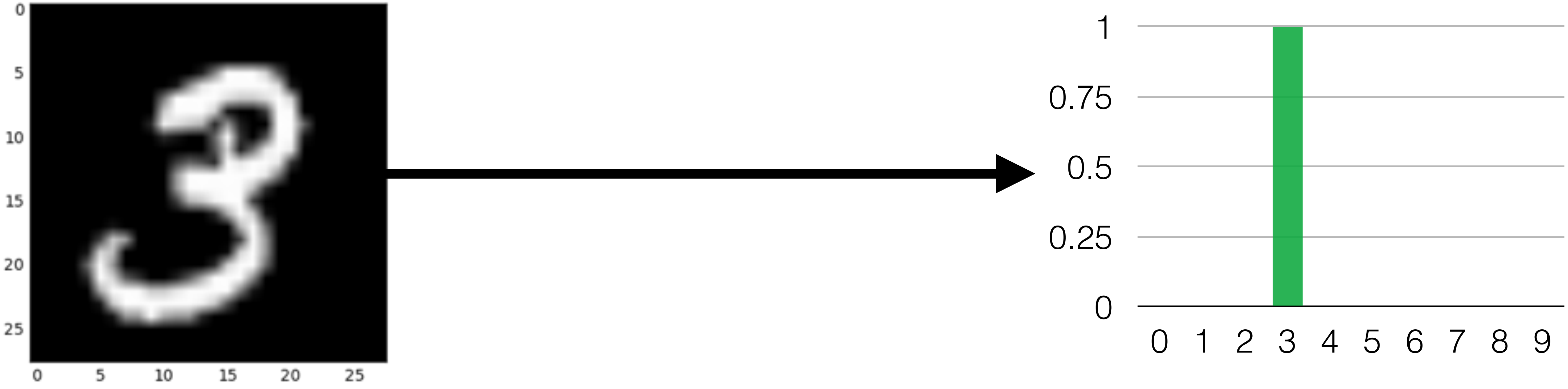


$$\mathcal{M}$$



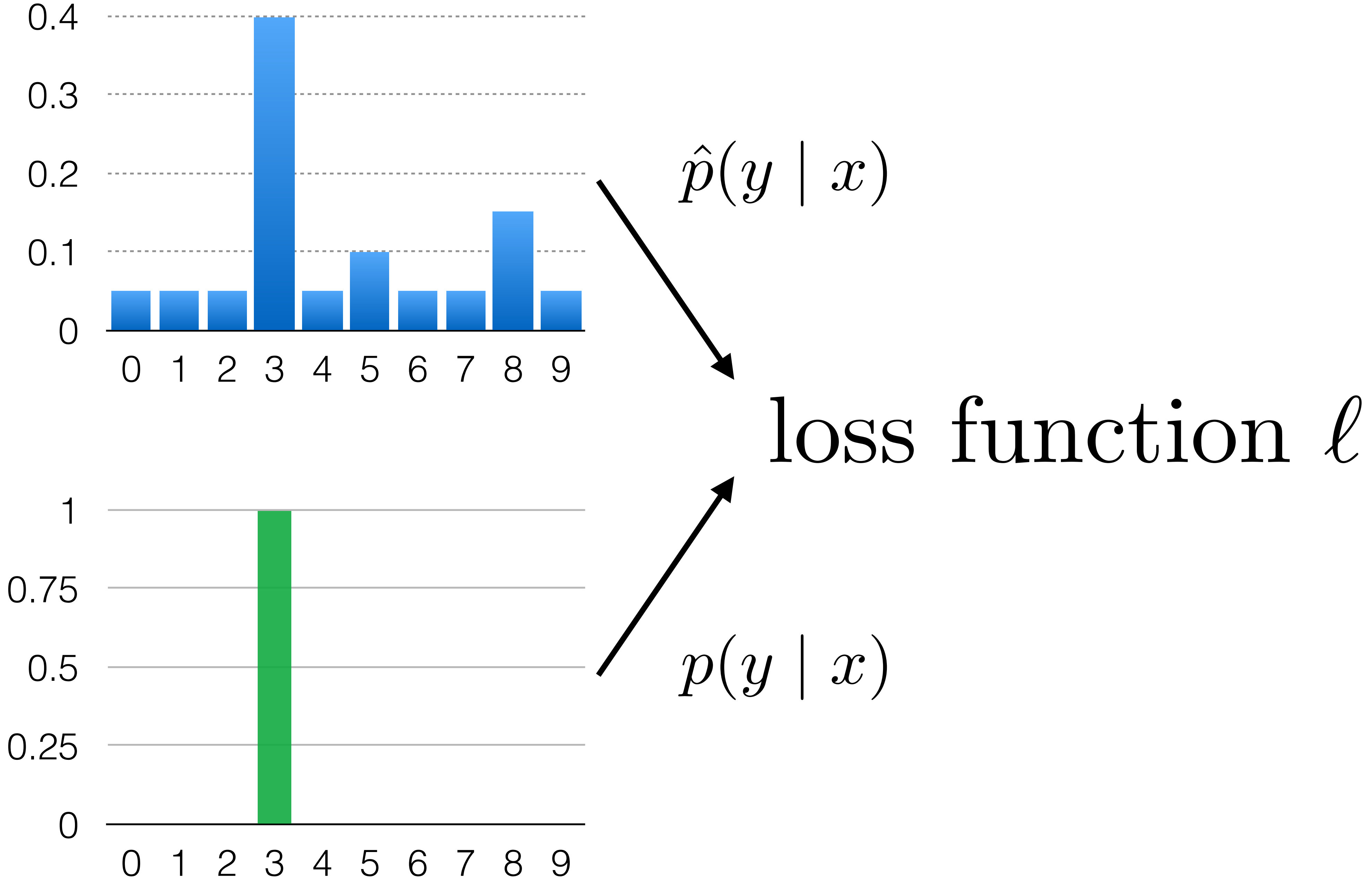
$$\hat{p}(y \mid x)$$

Supervised Learning



$$p(y \mid x)$$

Loss Function

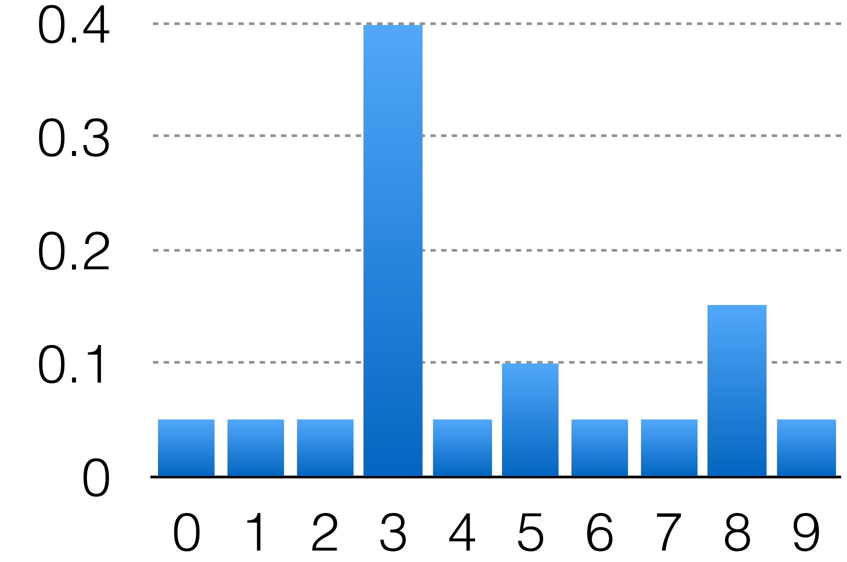


$\hat{p}(y \mid x)$

loss function ℓ

$p(y \mid x)$

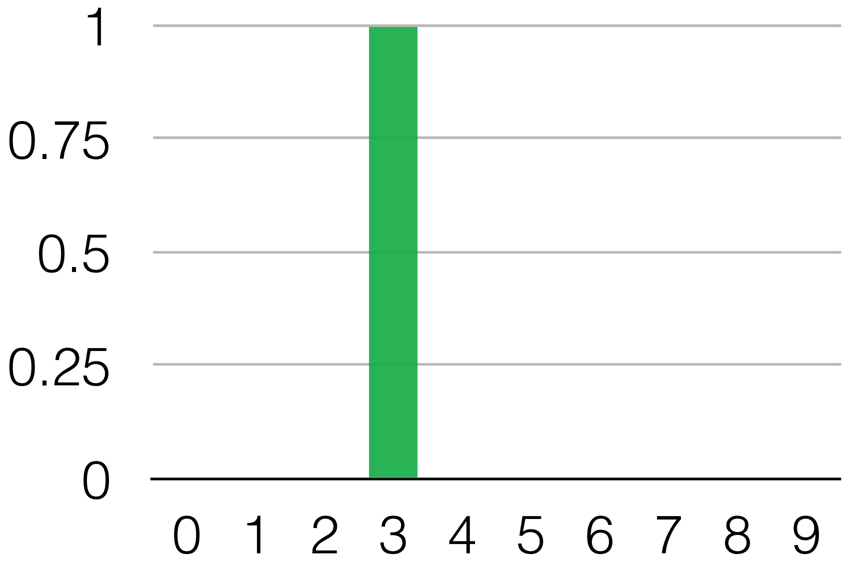
Cross Entropy Loss



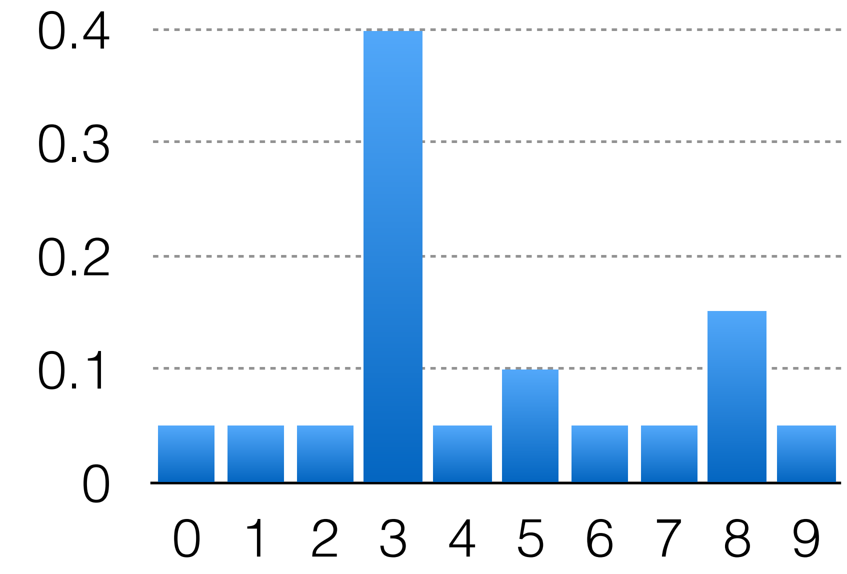
$\hat{p}(y \mid x)$

$$\ell = -\sum_{y \in \{0,1,\ldots,9\}} p(y \mid x) \log \hat{p}(y \mid x)$$

$p(y \mid x)$



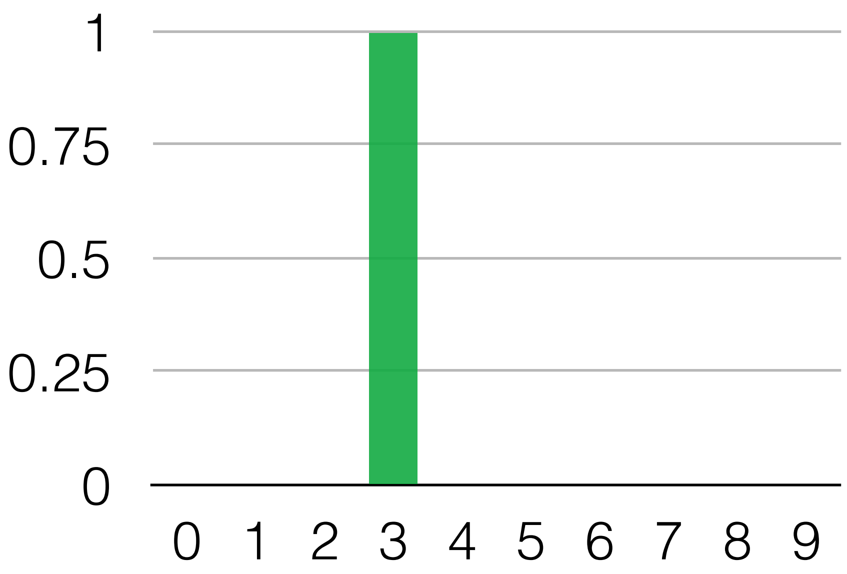
Cross Entropy Loss



$$\hat{p}(y \mid x)$$

$$\ell = -\log \hat{p}(y^* \mid x) \qquad y^* = 3$$

$$p(y \mid x)$$



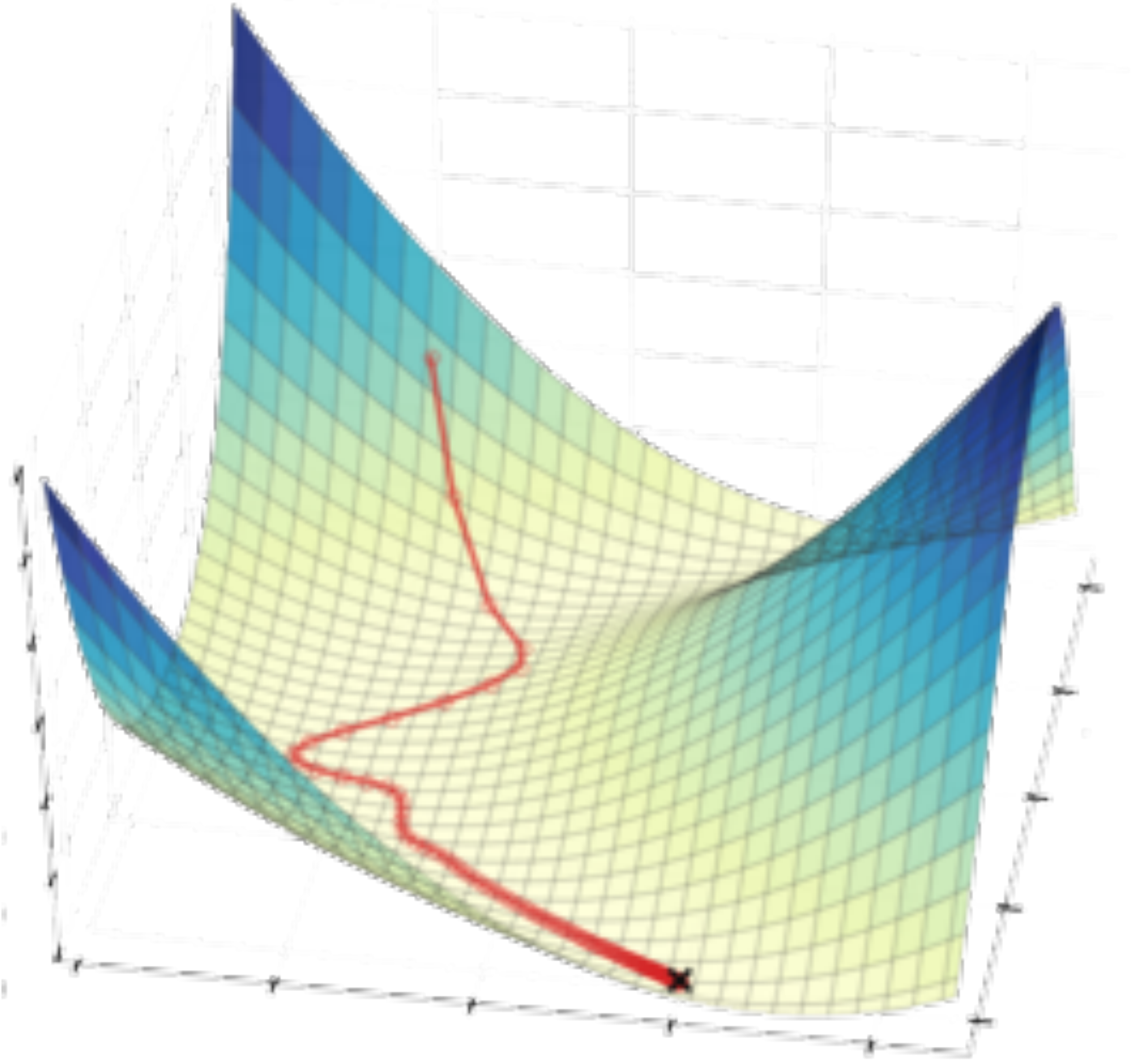
Gradient Descent

$$\ell = -\log \hat{p}_\theta(y^* \mid x)$$

$$\theta \leftarrow \theta - \eta \nabla_\theta \ell$$

$$\ell = -\frac{1}{N} \sum_{n=1}^{N} \log \hat{p}_\theta(y_n^* \mid x_n)$$

$$\ell = -\frac{1}{B} \sum_{n=1}^{B} \log \hat{p}_\theta(y_b^* \mid x_b)$$



Logistic Regression

$$\mathcal{M}$$

$x \in \mathbb{R}^D$

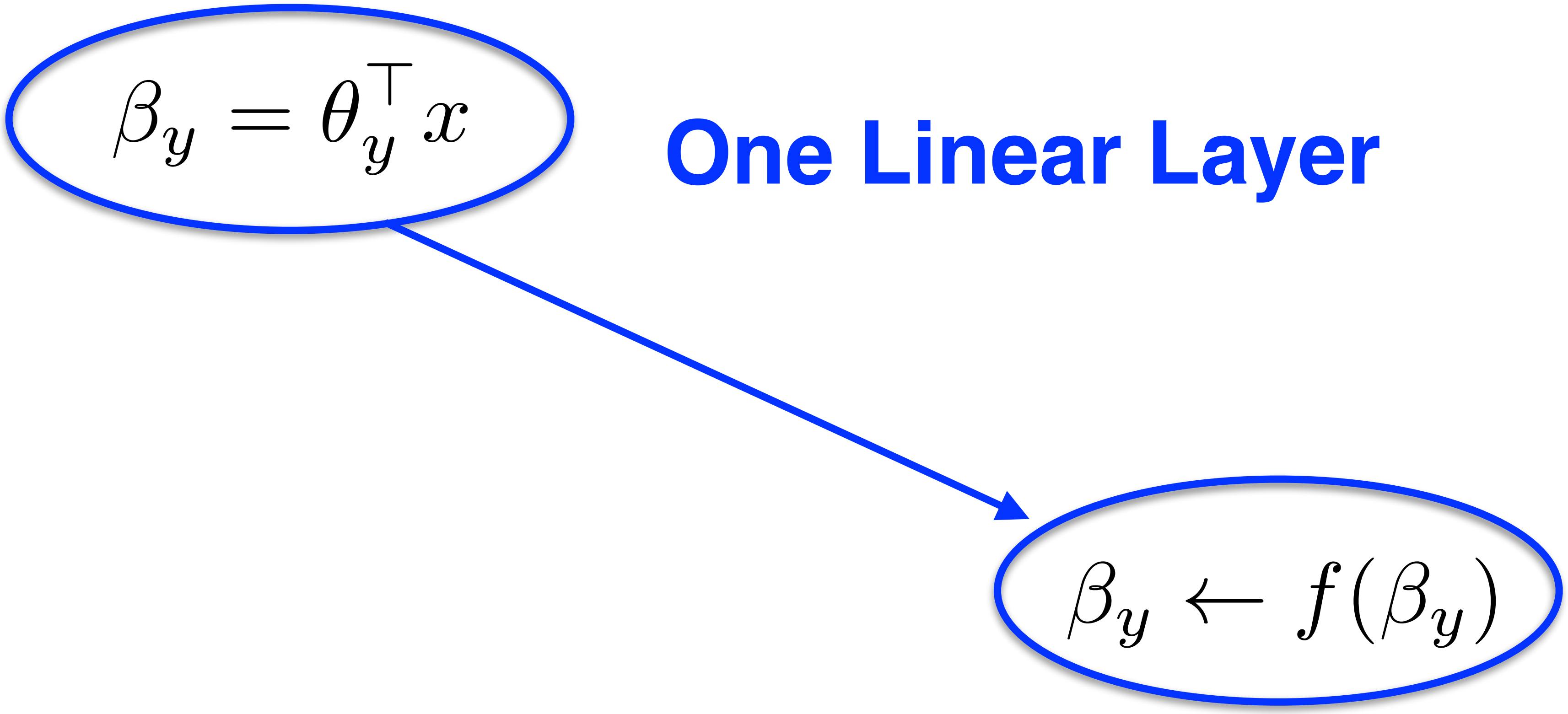
$\beta_y = \theta_y^\top x$

$$\hat{p}_\theta(y \mid x) = \frac{\exp(\beta_y)}{\sum_{y \in \{0,1,\ldots,9\}} \exp(\beta_y)}$$

Softmax Function

Multi-Layer Perceptron

$$\mathcal{M}$$



$$\beta_y = \theta_y^\top x$$

One Linear Layer

$$\beta_y \leftarrow f(\beta_y)$$

One Non-Linear Layer

Multi-Layer Perceptron

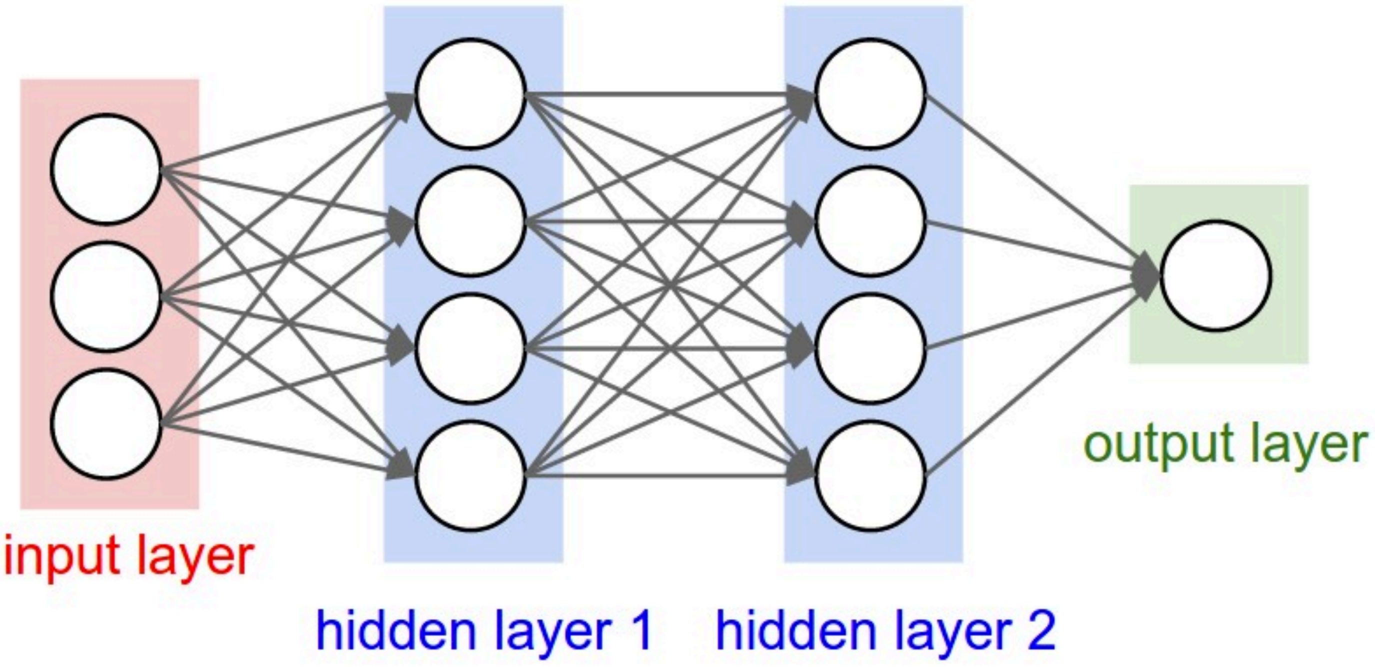
$$\mathcal{M}$$

$$\beta_y = \theta_y^\top x$$

One Linear Layer

$$\beta_y \leftarrow f(\beta_y)$$

One Non-Linear Layer



MXNet Gluon

Let’s make this cool stuff now!

Documents: Dope

Examples: IPython Notebooks